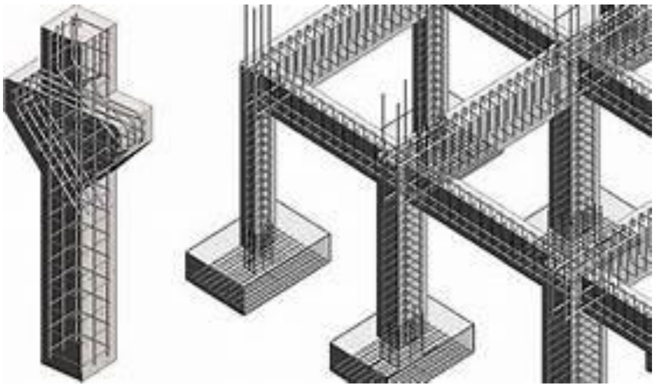
- optimization techniques Project

OPTIMIZING COST AND CO_2 EMISSION DURING CONSTRUCTION PROCESS



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Justification for the choice

The growing global **climate change** with the progress of human activity and rapid industrialization has created a need to appraise the impact of the products used in construction process and has challenged many contractors and companies to come up with more environmentally friendly ways of construction. The Intergovernmental Panel on Climate Change [1] reported that carbon dioxide makes up approximately 77% of greenhouse gases in which construction industry has a remarkable contribution.

Concrete as the most popular manufactured product with sustainability benefits, including considerable compressive strength and durability, excellent thermal mass, and long service life, contributes 5% of annual anthropogenic global CO2 production. Main contributor for it to happen is chemical conversion process used in the production of Portland clinker and cement production by fossil fuel combustion.

1.Introduction

The concrete industry is consuming a large amount of raw materials each year. Thus, besides cement's role in CO2 emission, mining, processing, and transporting of raw materials consume energy in large quantities and adversely affect theology of the planet [2]. Reducing then atmospheric concentration of CO2 caused by construction industry can be reached through innovative architecture, sustainable structural design, and reducing the cement of concrete mixture [3].

The purpose of this project is to present an optimal design technique of cost and CO2 emissions in order to achieve more sustainable, environmentally friendly, and economically feasible structural design. To do so we will use metaheuristic methods, these methods provide the practical possibility to improve the design process without the need for complex analysis; however, they require a great computational effort because of a large number of iterations needed for the evaluation of objective functions and structural constraints.

The optimization is carried out using enhanced colliding bodies optimization (CBO) algorithm developed by Kaveh and Ilchi Ghazaan [4] based on the improvement of CBO performance originally developed by Kaveh and Mahdavi [5] using memory to preserve some historically best solutions.

2. *Clarification of the problem*

As mentioned above, CO2 emissions of construction industry or building sector comprise relatively large portion of total CO2 emissions. Thus attention to the preservation of environment and reducing CO2 emissions has been the focus of studies in optimum design of RC structures. Those studies based methods of structural optimization can be divided into two categories: exact methods and approximate methods.

The exact methods are based on mathematical programming techniques such as the Lagrangian multipliers method, convex programming, linear programming, and sequential unconstrained minimization for which the required computational cost for finding an optimal solution grow polynomially with problem size, hence the applications of the exact methods are limited to simple and deterministic polynomial problem instances. To overcome these problems, metaheuristic methods are developed.

3. *Enlargement perspectives*

Today we face a huge problem that affects life on earth which is climate change. In this perspective, the present project-that aim for optimizing cost and CO2 emission of reinforced concrete- can play a considerable role in keeping our environment safe for us and for the next generations.

In fact, reducing CO2 emission during construction process gives the structural design office or the society concerned by the construction a large amount of environmental and economic advantages in **Carbon market**:

Under Carbon trading, a society or an office having fewer emissions sells the right to emit carbon to other societies or offices. The polluting entities emitting more carbon thereby satisfy their carbon emission requirements, and the trading market results in the most cost-effective carbon reduction methods being exploited first.

4. Formulation of the reinforced concrete Frame Optimization Problem

4.1. Structural Constraints

Structural constraints are a series of restrictions in terms of the limitations and specifications provided by the ACI code. The use of exponential penalty function allows us to enforce the constraint on the objective function. To compute the capacity constraints violation, the internal forces by the action of the vertical and horizontal loads upon the RC element are required. By summing over the different constraints either in terms of capacity or geometry, the total penalty of each design can be expressed as:

$$f_{\mathrm{p}}(x) = \left(1 + \sum_{i=1}^{n} \max(0, C_i(x))\right)^k$$

where x is the vector of design variables that are taken as the area of steel and the geometry of cross sections of beams and columns, Ci is the normalized degree of violation of the i th constraint, n is the number of constraints, and k>0 is a penalty exponent required for tuning the penalty function.

4.1.1. Beam Constraints

The moment capacity penalty can be expressed in normalized form as below:

$$C_1 = \frac{|M_{\mathrm{u}}| - \varnothing M_{\mathrm{n}}}{\varnothing M_{\mathrm{n}}}$$

where Mu is the ultimate applied moment and ∅ is the strength reduction factor. In order to prevent the possibility of sudden failure and improve the cracking behavior, the lower bound of reinforcement ratio is limited to:

$$\rho_{\mathrm{min}} = \frac{\sqrt{f'_{\mathrm{c}}}}{4 f_{\mathrm{y}}} \geq \frac{1.4}{f_{\mathrm{y}}}$$

The minimum reinforcement ratio penalty is:

$$C_2 = \rho_{\mathrm{min}} - \rho$$

The upper bound on the reinforcement ratio is limited to:

$$\rho_{\mathrm{max}} = 0.85 \beta_1 \frac{f'_{\mathrm{c}}}{f_{\mathrm{y}}} \frac{600}{600 + f_{\mathrm{y}}}$$

The maximum reinforcement ratio penalty is:

$$C_3 = \rho - \rho_{\mathrm{max}}$$

the beams are considered as non-prestressed at both continuous ends with allowable thickness of:

$$h_{\min} = \frac{l}{21}$$

where l is the span of the beam. The penalty for the thickness of the beam can be expressed as:

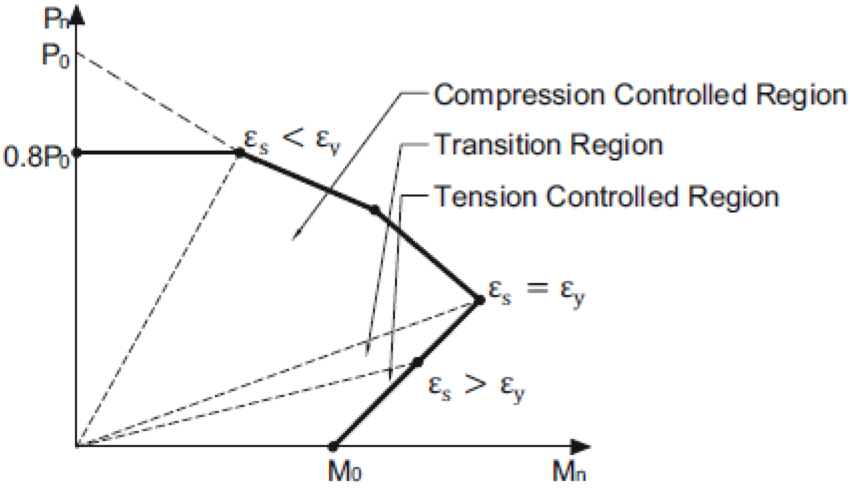
$$C_4 = \frac{h_{\min} - h}{h_{\min}}$$

4.1.2. Column Constraints

A column section is acceptable when the design action effects - defined by combination of the nominal moment capacity for the specified strain distribution and the nominal axial load capacity - fall within the load moment interaction diagram. The load moment interaction penalty can be expressed as:

$$C_5 = \frac{r - r_0}{r_0}$$

where r is the radial distance between the origin of the interaction diagram and the corresponding pair under the applied loading and r0 is the radial distance between the origin of the interaction diagram and the intersection of vector r with the load–moment curve.


Pn
P0
0.8P0
$\varepsilon_s < \varepsilon_y$
Compression Controlled Region
Transition Region
Tension Controlled Region
$\varepsilon_s = \varepsilon_y$
$\varepsilon_s > \varepsilon_y$
M0
Mn

Column load–moment interaction diagram

For compression members, the minimum longitudinal reinforcement $\rho_{\min}$ is limited to 0.01. The minimum reinforcement penalty is :

$$C_6 = \rho_{\min} - \rho$$

For compression members, the maximum longitudinal reinforcement $\rho_{\max}$ is limited to 0.08. The maximum reinforcement penalty is:

$$C_7 = \rho - \rho_{\max}$$

5. Formulation of the Optimization Problem

5.1. Objective Functions

The optimal design criterion for reinforced concrete frames involves two different objective functions: The first objective function is based on the most economical solution that accounts for the cost of materials in terms of the concrete, the steel, and the labor cost in construction process. The second objective function quantifies the embedded CO2 resulting from the use of materials, which involve emissions at different stages of the production and the placement of concrete and steel in structure. The unit costs and CO2 emissions were obtained from the 2007 database of the Institute of Construction Technology of Catalonia [6]. The general form of the objective function can be expressed as :

$$\min : f(x) = \sum_{i=1}^{n} u_i m_i (x_1, x_2, \ldots, x_r)$$
$$\text{s.t. } C_i(x_1, x_2, \ldots, x_r) \leq 0$$

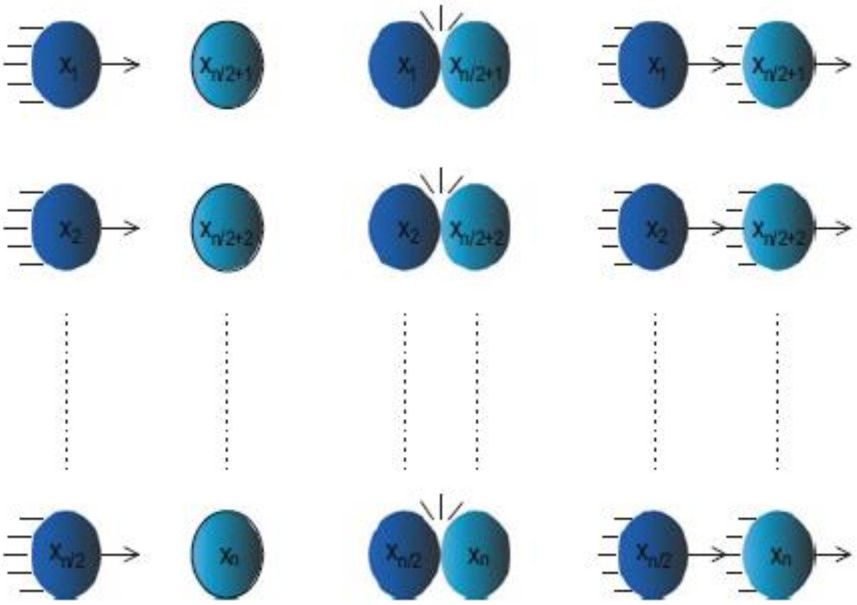
where u_i represents the unit prices or unit CO2 emissions of material and construction components, m_i is the measurements of the construction units, x_i are the design variables, n is the number of construction members, r is the number of design variables, and C_i (i=1, 2, . . ., n) are the design constraints.

5.1.1. Proposed Metaheuristic Algorithm

Metaheuristic algorithms are often based on the simulation of natural evolution and the principle of preservation or the survival of the fittest, which is a hypothetical population-based optimization procedure. In other words, a metaheuristic algorithm is an iterative process, which applies a set of agents to move through the design space and seek near-optimal solutions of the complex problems in a reasonably practical timescale. Although these optimization algorithms are usually nondeterministic, they make a reasonable trade-off between randomization and local search, this is why they can be used to find good feasible solutions in an acceptable time especially in case of intractable real-world problems. This project presents the application of a novel population-based stochastic algorithm so-called CBO which simulates a fundamental law of physics, namely collision between two bodies.

5.1.1.1. Enhanced Colliding Bodies Optimization Method

Collision is a short-term interaction between two bodies in which they are pushed away from each other and tend to form the most stable configuration and achieve the lowest energy state. According to the law of energy and momentum conservation, in all collisions the total amount of momentum possessed by the two objects does not change, i.e., the amount of momentum gained by one object is equal to the amount of momentum lost by the other object while the total kinetic energy after the collision may not be equal to the total kinetic energy before the collision and it changes to some other form of energy. What distinguishes different types of collisions is whether they conserve kinetic energy. When the total kinetic energy of system is lost, a perfectly inelastic collision occurs in which the two bodies stick together after the impact. Contrariwise if the total kinetic energy of system is conserved, a perfectly elastic collision occurs. The plot for this configuration is shown ithe figure below .



The collision between the sorted pairs of CBs

In terms of this conception, the search ability of the CBO algorithm can be framed based on the interaction between colliding bodies (CBs) that are moving through predefined amplitude, starting with random initial positions to find near optimal solutions. Each colliding body, as a solution candidate, contains a number of decision variables and is characterized by its position and velocity. The laws of energy conservation as well as linear momentum conservation allow us to adjust the changes of these attributes in two-body collisions.

The magnitude of the body mass for each CB is defined in association with the respective fitness value given as:

$$m_i = \frac{\frac{1}{\mathrm{fit}(i)}}{\sum_{j=1}^{n} \frac{1}{\mathrm{fit}(j)}} \qquad i = 1, 2, \ldots, n \tag{1}$$

where fit is the objective function value of the CBs and n is an even number of colliding bodies. In order to select pairs of objects for collision, CBs are sorted according to the value of their objective function in an increasing order and divided into two equal groups. Agents with upper fitness values (moving objects) and finite speed push the corresponding agents with lower fitness values (stationary objects), which are at rest before the collision, toward better positions. The velocity of moving bodies before the collision is given as:

$$v_i = x_i - x_{i-\frac{n}{2}} \qquad i = \frac{n}{2} + 1, \ldots, n \tag{2}$$

where x_i is the position vector of the ith CB in moving group and $x_{i-n/2}$ is the corresponding position vector in the stationary group.

After the collision, the attributes of each moving object are updated as follows:

$$v'_i = \frac{\left(m_i - \varepsilon m_{i-\frac{n}{2}}\right) v_i}{m_i + m_{i-\frac{n}{2}}} \qquad i = \frac{n}{2} + 1, \ldots, n \tag{3}$$

$$x'_i = x_{i-\frac{n}{2}} + r v'_i \tag{4}$$

where mi is the mass of the ith moving CB, v_i is the velocity of the ith moving CB before the collision, $m_{i-n/2}$ is the mass of the ith stationary CB, $x_{i-n/2}$ is the previous position of the ith stationary CB, r is a random vector uniformly distributed in the range of (-1,1), and ε represents the coefficient of restitution defined as :

$$\varepsilon = 1 - \frac{iter}{iter_{max}} \tag{5}$$

where iter is the number of iterations. Adjustment of this indicator changes the rate of intensification and diversification in the system and generally ranges between zero and one.

In addition, the attributes of each stationary object after the collision, which now has a velocity in the same direction of the moving object, are updated as follows

$$v'_i = \frac{\left(m_{i+\frac{n}{2}} + \varepsilon m_{i+\frac{n}{2}}\right) v_{i+\frac{n}{2}}}{m_i + m_{i+\frac{n}{2}}}, \qquad i = 1, \ldots, \frac{n}{2} \tag{6}$$

$$x'_i = x_i + r v'_i \tag{7}$$

Where mi is the mass of the ith stationary CB, $m_{i+n/2}$ is the mass of the ith moving CB, $v_{i+n/2}$ is the velocity of the ith moving CB before the collision, and x_i is the previous position of the ith stationary CB.

Historical best solutions are saved by employing the colliding memory (CM) which stores some best solutions of each iteration found in previous population and substitutes them with some current worst CB vectors.Introducing new best bodies into the population prevents the population from moving only to neighboring states and speeds up the convergence rate without increasing the computational cost.

In order to break one or more members of the population out of local minima and produce a more efficient search, one component of the ith CB is regenerated in a random manner in any given generation. The probability of choosing the component is expressed as Pro, which ranges between (0, 1).

In accord with the given definition, enhanced colliding bodies algorithm is a continuous variable-based method improved by saving the best solutions and regenerating random members of population occasionally to produce a more efficient and reliable solution. The steps of this algorithm can briefly be outlined as follows:

Step 1: Randomly initialize the vector of CBs with n variables and evaluate their associated fitness function.

Step 2: Store some best solutions of each iteration in the colliding memory and replace them with the current worst CB vectors.

Step 3: Calculate the mass value for each CB using Eq.(1).

Step 4: Sort the fitness value of the objective function for each CB in an increasing order, and then determine the pairs of CBs for collision.

Step 5: Evaluate the velocity of moving bodies before the collision using Eq.(2)

Step 6: Update the velocities of stationary and moving bodies after the collision using Eqs. (6) and (3), respectively.

Step 7: Update the positions of stationary and moving bodies using the generated velocities after the collision in step 6 and Eqs. (7) and (4), respectively. If some bodies' new positions violate the boundaries, correct their position and return to the specified domain.

Step 8: Compare Pro with a random number, rn_i (i=1, 2 . . . n), which is distributed uniformly between (0, 1), if rn_i <pro, randomly select a CB from both moving and stationary group and regenerate one related component accidentally.

Step 9: Return to Step 2 until a terminating criterion is satisfied.

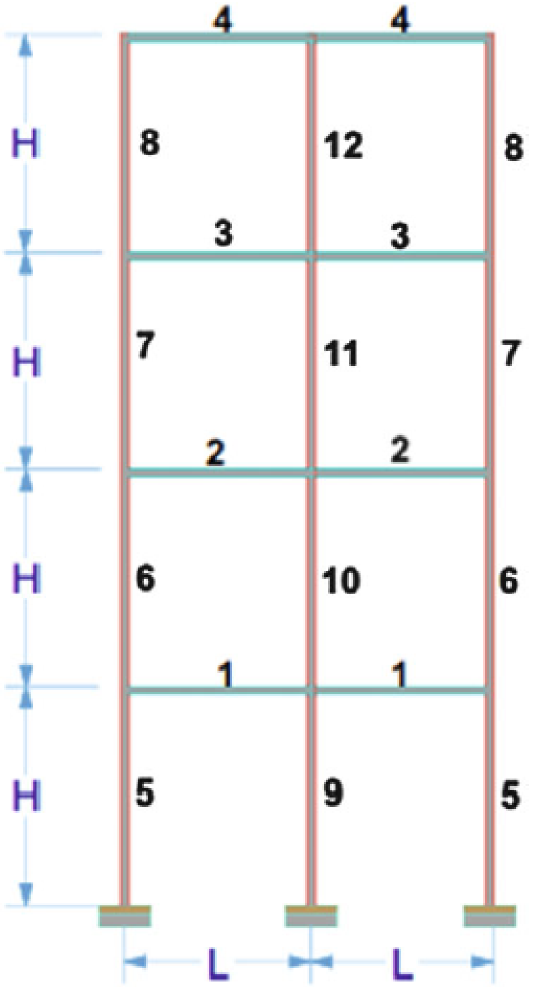
6. Design Example

In order to demonstrate the efficiency and performance of the proposed algorithm. A problem of two-bay four-story of reinforced concrete frame is adabted and solved by Kaveh and Ardalani S [6 using the ECBO algorithm .This problem was presented by Paya-Zaforteza et al. [7] and redesigned by Camp and Huq [8].

6.1. Two-Bay Four-Story Frame

The figure below illustrates the two-bay four-story frame originally designed by Paya- Zaforteza et al. [6] using SA algorithm and redesigned by Camp and

Huq. [7] using BB–BC algorithm. The height of each story is 3 m, and the span of each bay is 5 m. The optimal dimension of width for beam and column sections is considered between (150, 1200) mm and (250, 1200) mm, respectively. The step of increment for beam sections is 10 mm and for column sections is 50 mm. As shown in the figure, the frame is consisted of 8 beams and 12 columns arranged in 4 beam groups and 8 column groups.



Two-bay four-story RC plane frame

The spacing considered between adjacent parallel frames is 5.00 m, and the thickness of the slab for all stories is 290 mm. Twelve load combinations that include counteracting effects of dead, live, and wind loads are taken into account to determine the required strength of the members as listed below:

Table 4.1 The applied Loads on the frame

Action	Value
DL in story 1–3 (kN/m^2)	4
DL in story 4 (kN/m^2)	6
LL in story 1–3 (kN/m^2)	3
LL in story 4 (kN/m^2)	1
WL in story 1 (kN)	8.83
WL in story 2 (kN)	9.86
WL in story 3 (kN)	10.74
WL in story 4 (kN)	5.81

$$\begin{aligned} U &= 1.5D & U &= 1.5D + 1.44L1 + 1.44W1 \\ U &= 1.5D + 1.6L1 & U &= 1.5D + 1.44L2 + 1.44W1 \\ U &= 1.5D + 1.6L2 & U &= 1.5D + 1.44LT + 1.44W1 \\ U &= 1.5D + 1.6LT & U &= 1.5D + 1.44L1 + 1.44W2 \\ U &= 1.5D + 1.6W1 & U &= 1.5D + 1.44L2 + 1.44W2 \\ U &= 1.5D + 1.6W2 & U &= 1.5D + 1.44LT + 1.44W2 \end{aligned}$$

where D is the uniform dead load applied to each beam, L1 stands for the live load applied to only one beam in each story while the bays change alternatively, L2 is the uniform live load applied in a pattern opposite of L1, W1 is the wind load applied to the left side of the frame, and W2 is the wind load applied to the right side of the frame. Table 4.1 above lists the values of the uniform loads and wind loads at each story. Compressive strength of concrete varies in each story from 25 to 50 MPa with the increment step of 5 MPa. The unit weight of concrete is 2323 kg=m3. Reinforcement has the yield strength of 500 MPa, and the unit weight of 7849 kg=m3. The number of DB sections created for beams and columns are 98,424 and 7584, respectively, which results in a design space of 2.23e60. The frame has a total of 60 design variables. Hence, the population of 16 CBs with a typical stopping criterion of 4000 was required.

In this example, two objective functions are implemented to minimize cost and CO2 emissions in terms of the materials and construction process. The general form of the cost function is defined as:

$$\begin{aligned} f_k = {} & \sum\nolimits_{i=1}^{n_b+n_c} \{C_c b_i h_i + C_s A_{si}\} l_i + \sum\nolimits_{i=1}^{n_b} \{C_f(b_i + 2(h_i - t_i)) + C_t b_i\} l_i \\ & + \sum\nolimits_{i=1}^{n_c} \{2C_f(b_i + h_i)\} l_i \end{aligned}$$

where C_t is the unit rate of scaffolding and ti is the thickness of the slab. The CO2 emission function has the same form of the cost function; however, the unit values are different and also the scaffolding term is not considered. The unit rates for cost and CO2 emissions are listed in Table 4.2 below:

Table 4.2 Unit prices and CO2 emissions

	Cost (€)		CO_2 (kg)	
Description	Beam	Column	Beam	Column
Steel B-500 (kg)	1.3	1.3	3.01	3.01
Concrete HA-25 (m^3)	78.40	77.80	132.88	132.88
Concrete HA-30 (m^3)	82.79	82.34	143.48	143.48
Concrete HA-35 (m^3)	98.47	98.03	143.77	143.77
Concrete HA-40 (m^3)	105.93	105.17	143.77	143.77
Concrete HA-45 (m^3)	112.13	111.72	143.77	143.77
Concrete HA-50 (m^3)	118.60	118.26	143.77	143.77
Form work (m^2)	25.05	22.75	3.13	8.90
Scaffolding (m^2)	38.89	–	4.86	–

6.1.1. Results

The results for single objective of cost function obtained by the proposed algorithm and the previous research works are compared in Table 4.3 . The best solution reported by the ECBO is 3429.92€ with 3587.88 kg of CO2 emissions. The best ECBO cost design is 3.13% less than the best solution given by BB–BC. Concrete represents 18.22% of the total cost, while reinforcing steel about 25.55% of the total cost. Table 4.4 compares the results for single objective of CO2 emission functions. The best solution reported by the ECBO is 3238.25 kg with a cost of 3525.27€. The best ECBO CO2 design is 2.67% less than the best solution given by BB–BC. The percentage comparison of the solutions indicates that the best CO2 emission design decreased the CO2 emissions by 9.74% with a slight increase in cost of 2.77 %. Since more environmentally friendly solutions are recommended by IPCC, on the other hand, the low-CO2 emission design could decrease the CO2 emissions considerably at an acceptable cost increment in practice; it seems that designing the RC structures based on the CO2 emissions is more logistical (Table 4.5). Figure 4.2 compares the strength ratio in element groups for both cost and CO2 objective functions. As can be seen, in beam groups the use of section capacity in low-cost design is lower than low-CO2 emission design,while in column groups the use of section capacity is higher. This finding shows that there is a relationship between the geometry of frame and the objective functions.

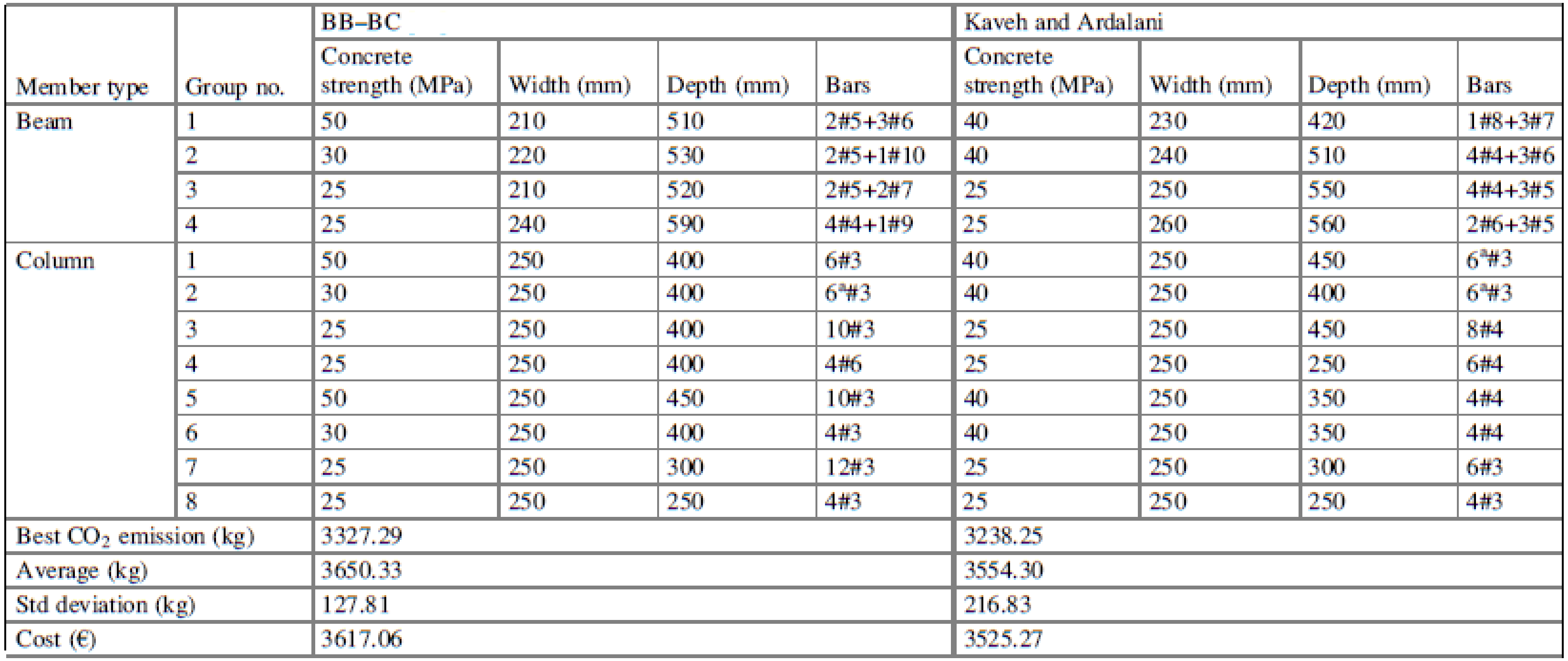
In Table 4.6, the percentage of cost and CO2 emissions is quantified for materials and construction components. Concrete, reinforcing steel, formwork, and scaffolding represent approximately 26, 18, 46, and 10% of the total cost and 50, 35, and 15% of the total emissions, respectively.

Table 4.7 summarizes the results of the ECBO single-objective designs. The best ECBO design with lower cost is 3490€ with 3475 kg of CO2 emissions. Alternatively, the best ECBO design with lower emissions is 3318 kg with a cost of 3520€ . All these lead to a tentative conclusion that the CO2 and cost objectives should be considered together in RC structural designs. The Pareto front is presented in Fig. 4.3

Table 4.3 Design results for cost objective for two-bay four-story frame

Member type	Group no.	BB–BC				Kaveh and Ardalani			
		Concrete strength (MPa)	Width (mm)	Depth (mm)	Bars	Concrete strength (MPa)	Width (mm)	Depth (mm)	Bars
Beam	1	40	180	430	1#8+2#8	30	220	430	2#7+3#7
	2	40	180	450	1#10+2#8	30	250	450	2#7+4#5
	3	30	190	460	1#8+1#11	30	220	440	3#6+3#6
	4	25	220	530	4#4+1#10	25	220	430	1#9+3#7
Column	1	40	250	550	6#5	30	300	500	8#3
	2	40	250	300	4#5	30	300	400	6#4
	3	30	250	300	4#6	30	250	350	8#3
	4	25	250	300	6#6	25	250	350	12#4
	5	40	250	300	4#5	30	300	450	6[a]#4
	6	40	250	250	8#5	30	250	250	4#4
	7	30	250	250	6#4	30	250	300	4#3
	8	25	250	250	4#3	25	250	250	4#3
Best cost (€)		3540.88				3429.92			
Average (€)		3790.25				3682.09			
Std deviation (€)		139.28				156.51			
CO_2 emission (kg)		3778.24				3587.88			

Table 4.4 Design results for CO2 objective for two-bay four-story frame



Member type	Group no.	BB–BC				Kaveh and Ardalani			
		Concrete strength (MPa)	Width (mm)	Depth (mm)	Bars	Concrete strength (MPa)	Width (mm)	Depth (mm)	Bars
Beam	1	50	210	510	2#5+3#6	40	230	420	1#8+3#7
	2	30	220	530	2#5+1#10	40	240	510	4#4+3#6
	3	25	210	520	2#5+2#7	25	250	550	4#4+3#5
	4	25	240	590	4#4+1#9	25	260	560	2#6+3#5
Column	1	50	250	400	6#3	40	250	450	6^{a}#3
	2	30	250	400	6^{a}#3	40	250	400	6^{a}#3
	3	25	250	400	10#3	25	250	450	8#4
	4	25	250	400	4#6	25	250	250	6#4
	5	50	250	450	10#3	40	250	350	4#4
	6	30	250	400	4#3	40	250	350	4#4
	7	25	250	300	12#3	25	250	300	6#3
	8	25	250	250	4#3	25	250	250	4#3
Best CO_2 emission (kg)		3327.29				3238.25			
Average (kg)		3650.33				3554.30			
Std deviation (kg)		127.81				216.83			
Cost (€)		3617.06				3525.27			

Table 4.5 Ratio between Cost and CO2-optimized design variables

Group no.	Frame characteristics	
	Concrete strength	Area of elements
1	0.75	0.97
2	0.75	0.91
3	1.2	0.70
4	1	0.64
5	0.75	1.33
6	0.75	1.20
7	1.2	0.77
8	1	1.40
9	0.75	1.54
10	0.75	0.71
11	1.2	1
12	1	1

Fig.4.2 Strength ratios in element groups for both cost and CO2 objective functions

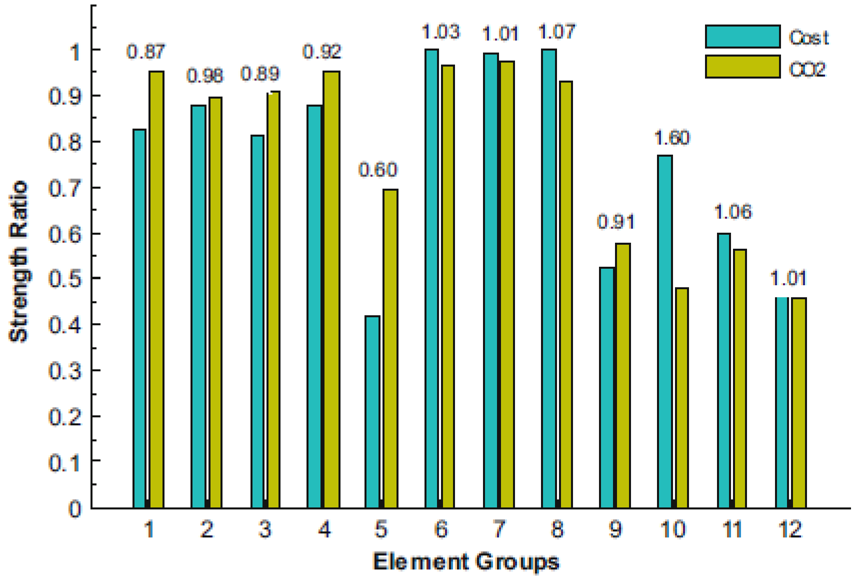


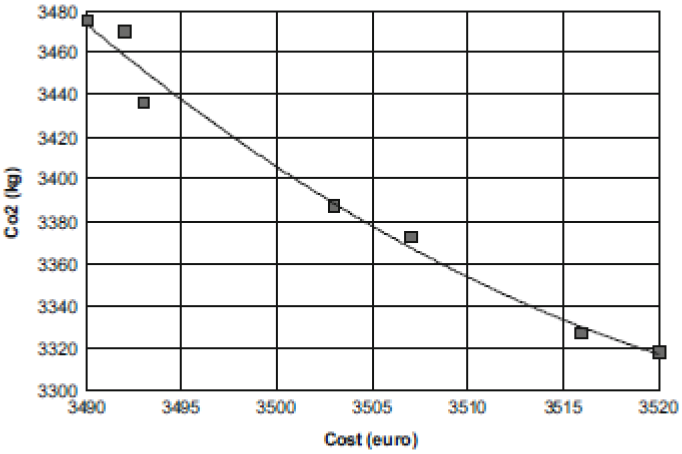
Table 4.6 Percentage of total cost and CO2 emissions

Description	Cost (%)			CO$_2$ (%)		
	Beam	Column	Total	Beam	Column	Total
Steel	70	30	26	70	30	50
Concrete	52	48	18	60	40	35
Form work	33	67	46	18	82	15
Scaffolding	10	–	10	–	–	–
Total			100			100

Table l4.7 Results of the ECBO single-objective design

Objective	Cost (€)	CO$_2$ (%)
ECBO-Cost	3490	3475
ECBO-CO$_2$	3520	3318

Fig.4.3 ECBO Pareto front



7. Concluding remarks

This project aimed to evaluate the usefulness of the ECBO through the optimization of multistory-multi-bay frames including architectural and reinforcement detailing. The algorithm is applied to two objective functions: the cost of material and the embedded CO2 emissions during the construction process. Based on the present work, the following conclusions can be derived:

1. The ECBO design improved the results from both objective functions in a reasonably practical time over the designs developed by the BB–BC algorithm. Moreover, in comparison with other evolutionary approaches, the ECBO algorithm is simple to implement and it requires a few parameters to be set. These findings proved that ECBO-based methodology could be applied as an effective and powerful algorithm to arrive at a realistic design solution for real complex problems.
2. Conclusive solution of the algorithm is improved through selecting more rational groups of the elements. This implies that grouping in which the members in the same group are similar in the internal force distribution results in more economical solutions.

8. Implementation in Morocco

According to a study conducted by Climate Action Tracker as part of the COP21 being held in Paris between November 30 and December 11, Morocco, along with Bhutan, Ethiopia and Costa Rica earned the classification as the greenest countries in the world [9]. Besides at the sidelines of the Global NDC Conference in May 2017 in Berlin Mr. Mohamed Nbou, Director in the Ministry of Environment of Morocco, declared that Morocco aim to reduce CO2 emissions by 34 % compared to business as usual by 2030. *[10]*

From those information we can relate that the implementation of the optimization method we talked about previously is possible and would be welcomed by the authorities and the government. Many measures could be taken like reducing taxes for technical office and companies that use that optimization methods. And as a results CO2 emission will decrease enormously because cement and construction sectors are classified among the first pollutant sectors around the world.

9. Technical Office or a big company?

Personally, I think that optimizing cost and CO2 emission of reinforced concrete should be assigned to a structural study office, because such a tasks falls within its speciality.

The technical office has engineers and technicians well trained, experienced, and specialized in the calculation, design, and the sizing of reinforced concrete.

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